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From purchase to return: How personalized E-commerce recommendations shape consumer behavior

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ABSTRACT

As fashion e-commerce grows, personalized recommendation systems (PRS) are increasingly influential in shaping consumer decisions. Based on the DeLone and McLean IS Success Model, this study investigates how information, system, and service quality-along with immersion-affect perceived value, purchase intention, post-purchase satisfaction, and return intention. Using data from 299 online fashion shoppers and PLS-SEM analysis, the findings highlight perceived value as a key dual mediator: it partially mediates the effects of PRS quality on purchase intention and fully mediates the effect of immersion on purchase intention. While PRS quality and immersion enhance perceived value, only system and service quality directly influence purchase intention. However, neither perceived value nor purchase intention significantly affects post-purchase satisfaction, revealing a gap between expectation and experience. Post-purchase satisfaction is the sole significant predictor of return intention, with dissatisfaction driving returns. These results underscore the need for e-commerce platforms to align recommendation strategies with accurate product representation to reduce returns and build lasting trust.

1. Introduction

Since the emergence of the digital era in 1989, the advancement of information technology has systematically altered human lifestyles and propelled the transformation of business paradigms. With the swift progression of the Internet and digital technologies, e-commerce has emerged as an essential element of the global economy. E-commerce not only overcomes the geographical constraints of traditional brick-and-mortar stores and reduces fixed costs but also provides diverse information presentation methods, enabling businesses to operate in a more competitive environment (Debruyne and Tackx, 2019). Fueled by advancements in technologies including artificial intelligence (AI), extensive data analytics, and cloud computing, enterprises are now able to meticulously scrutinize consumer behavior and provide tailored shopping experiences (Nash, 2019). Mobile commerce (M-commerce), facilitated by the widespread adoption of smart devices, has become a major driver of growth, further reshaping consumer purchasing patterns (Wei et al., 2002). Despite its strategic advantages, e-commerce faces key challenges, including product-expectation mismatches, the lack of tactile shopping experiences, high return rates, and the accuracy of personalized recommendations (Wilfling et al., 2022). Returns often stem from consumer uncertainty and can be seen as a "resistance" to unsatisfactory purchases (Fang et al., 2019). As online shopping matures and consumer choices expand, businesses must not only boost sales but also reduce returns to sustain customer satisfaction and brand loyalty (Odonkor, 2018). A report by Sina (2021) noted that return rates during the Double Eleven shopping festival reached 30 %, underscoring the complex link between purchase intention and return behavior (Guthrie et al., 2021). Thus, leveraging data technologies to better understand consumer needs and minimize unnecessary returns remains a critical challenge for e-commerce enterprises.

Recommendation systems utilize advanced machine learning techniques and comprehensive data analytics to deliver tailored recommendations, significantly contributing to the improvement of user experience and the overall efficacy of business operations within the realm of e-commerce. The principal categories of recommendation systems encompass content-based filtering, collaborative filtering, and hybrid filtering (Mohanty et al., 2022). These systems significantly improve sales conversion rates (Wu and Yang, 2024), help customers quickly find suitable products, and enhance customer satisfaction and loyalty (Hung and Huynh, 2019). Moreover, they contribute to increasing the average order value by recommending relevant products,

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thereby enhancing both cart value (Sisodiya, 2024) and overall user experience (Saxena, 2023). Additionally, they assist e-commerce businesses in optimizing inventory management and reducing the risk of unsold stock (Sharma et al., 2024). With advancements in artificial intelligence and big data analytics, modern recommendation systems have evolved beyond traditional purchase history analysis to incorporate user behavior, social data, and deep learning, enabling more precise recommendations (Dey et al., 2022). Thus, recommendation systems not only enhance consumers' shopping experiences but also serve as a critical technology for businesses to gain a competitive edge. Nevertheless, these systems can create concerns like filter bubbles and privacy risks, necessitating a balance between accuracy and transparency in system design (Ji, 2024).

The notion of recommendation systems can be traced to the 1990s, during which they predominantly utilized collaborative filtering methodologies to assist users in identifying pertinent content, including movies, music, or product suggestions (Markellou et al., 2005). However, with the exponential increase in data volume, conventional systems provided identical content to all users, frequently resulting in an overwhelming abundance of information and rendering it challenging for consumers to locate appropriate products with efficiency. With the proliferation of the Internet and the advancement of electronic commerce, personalized recommendation systems were developed in the early 2000s, becoming integral to the enhancement of consumer experiences within e-commerce platforms (Wei et al., 2002). These systems leverage data tracking, behavioral analysis, preference ranking, and machine learning to simulate "personal temptation" behavior found in physical retail environments, proactively offering tailored shopping recommendations (Balsarini et al., 2021). Notable applications include YouTube's personalized video recommendations, social media content feeds, and e-commerce platforms like Amazon and Taobao, where recommendation algorithms help consumers discover products more effectively. Personalized recommendations not only improve user experience by quickly matching consumers with relevant products (Gao and Wu, 2021) but also enhance sales conversion rates, increase purchase intention, and drive business revenue (Zhang and Cheng, 2024). Moreover, accurate recommendations reduce customer attrition, strengthen satisfaction and loyalty, and encourage repeat purchases (Han, 2019). Additionally, businesses can optimize inventory management through consumer trend analysis, ensuring smooth inventory turnover and improving operational efficiency (Wang and Wu, 2024). Overall, personalized recommendation systems have evolved into a crucial technology in e-commerce, enhancing both consumer shopping experiences and business performance by driving engagement, increasing sales, and improving operational effectiveness.

An examination of the prevailing literature indicates that scholarly inquiry into the utilization of personalized recommendation systems within the e-commerce sector predominantly centers on a number of critical domains, encompassing user data and behavioral patterns (Hussien et al., 2021; Zhang and Cheng, 2024; Zhang, 2024), social relationships (Bin, 2023), algorithmic approaches (Wang et al., 2020; Bin, 2023; Wang and Wu, 2024), system quality (Liu et al., 2017, 2021; Lu and Kim, 2023), data privacy and security (e.g., anonymization and encryption techniques) (Zhang and Cheng, 2024), machine learning and deep learning (Wang et al., 2018; Li et al., 2024; Kanth et al., 2024), and evaluative criteria for recommendation systems, including accuracy, recall, and conversion rates (Zhang & Li, 2023). However, the overwhelming focus of existing studies is on the impact of recommendation systems on buying intentions and customer contentment, while the investigation into their influence on return intentions is significantly limited. While some research suggests that high-quality recommendation systems can enhance immersion and improve the shopping experience, thereby shaping consumer behavior, their direct relationship with return behavior remains underexplored. Additionally, online shopping immersion is not only influenced by website design but also by the overall shopping environment and atmosphere, which serve as crucial factors (Kanwar et al., 2020). In particular, within the apparel industry, AI-powered virtual try-on solutions and AR/VR technologies have been demonstrated to effectively reduce return rates (Singh et al., 2023; Liu et al., 2020; Malleswararaoo, 2024; Pfeiffer, 2023).

This study focuses on apparel e-commerce due to its highly personalized purchasing decisions, high return rates, strong reliance on recommendation systems, and significant commercial value. Apparel purchases involve multiple factors-style, size, material, brand, and price-making the quality of personalized recommendations a critical determinant of consumer decisions (Subaranjani et al., 2024). Compared to standardized products such as books and electronic devices, apparel exhibits significantly higher return rates due to size mismatches, expectation discrepancies (e.g., differences in color and texture) (Tu and Dong, 2010), and impulse buying (Alghieth, 2020; Lu et al., 2019). Moreover, the vast variety and rapid turnover of apparel items often make it difficult for consumers to find suitable products in a short time, underscoring the essential role of personalized recommendations in improving search efficiency and facilitating purchasing decisions (Shilaskar et al., 2024). The behavior associated with apparel acquisition is significantly shaped by prevailing fashion trends, societal influences, and individual style inclinations, as demonstrated by the influence of social media platforms and the endorsements of Key Opinion Leaders (KOLs) in fashion choices (Rocha et al., 2017), along with the effects of seasonal variations and promotional activities (Agarwal et al., 2018). With the continuous expansion and strong growth potential of the global apparel e-commerce market (Yu et al., 2019), investigating how recommendation systems influence purchasing and return behaviors holds both academic and practical significance.

This study utilizes DeLone and McLean's (2003) Information Success Model to explore recommendation systems' effects on consumer behavior. It integrates immersion and return intention to analyze the connections among recommendation system quality, perceived value, immersion, and post-purchase behaviors. Specifically, this research explores how the quality of personalized recommendations influences consumer immersion in the shopping experience and how this, in turn, affects perceived value and return intentions. The results generated from this comprehensive research endeavor, which meticulously examines various facets of consumer behavior and technological interaction, possess the remarkable potential to provide substantial and meaningful insights specifically tailored for e-commerce platforms, thereby enabling the meticulous optimization of sophisticated recommendation algorithms, the significant enhancement of consumer engagement metrics, the strategic reduction of product return rates, and ultimately contributing to the overall augmentation of customer satisfaction levels across diverse market segments.

2. Literature examination and formulation of hypotheses

2.1. Information success model

Information systems (IS) serve as integrated platforms that synergize people, technologies, data, and organizational resources to support the collection, processing, storage, dissemination, and application of information-ultimately enabling strategic decision-making, operational efficiency, and business innovation (Wang and Zhu, 2025). The DeLone and McLean Information Systems Success Model is a prevalent framework for evaluating IS performance and value (Al-Fraihat et al., 2020). Originally proposed by DeLone and McLean (1992), the model outlines six fundamental dimensions to assess the success of information systems: information quality, system quality, system usage, user satisfaction, individual impact, and organizational impact. These dimensions together provide a multidimensional view of how effectively an information system contributes to both individual users and broader organizational goals. In response to technological advances and application diversity, the model was later revised to include service quality and intention to use, reflecting the growing importance of user experience and service support, particularly in web-based platforms (DeLone and McLean, 2003, 2004). The revised model suggests that information, system, and service quality together affect user intention and satisfaction, which in turn lead to net benefits as a measure of IS effectiveness (Petter et al., 2008; Kuo and Hsu, 2022). This framework has been validated across multiple domains, establishing a theoretical foundation for evaluating system efficacy, user experiences, and organizational outcomes.

2.2. Personalized recommendation system (PRS)

Personalized Recommender Systems (PRS) leverage machine learning and data mining to deliver tailored content based on users' behaviors, preferences, and demographics (Ricci et al., 2015). They are extensively utilized in the domain of electronic commerce (for instance, Amazon), digital streaming platforms (such as Netflix and Spotify), and social networking services (including YouTube and Facebook), online learning (e.g., Coursera, edX), and healthcare for personalized health recommendations (Jannach et al., 2010). The effectiveness of PRS is evaluated through key metrics, with recommendation accuracy being critical. It measures how well recommendations match user preferences, assessed via RMSE, MAE, HR, and NDCG (Gunawardana and Shani, 2015). Hybrid models that integrate content-based filtering (CBF) with collaborative filtering (CF) significantly augment precision (Adomavicius and Tuzhilin, 2011). Another essential factor is system trustworthiness, shaped by transparency, explainability, privacy protection, and consistency (Pu et al., 2011). Clear and credible explanations increase user trust and acceptance (Tintarev and Masthoff, 2015). Beyond accuracy and trust, user acceptance depends on recommendation relevance, usability, and diversity (Zanker et al., 2010). Both long-term behavior and short-term factors, like immediate needs and emotions, impact acceptance (Konstan and Riedl, 2012). Personalization degree also plays a role, as systems adjust recommendations based on location, time, and device type (Adomavicius and Tuzhilin, 2005). However, excessive personalization may create filter bubbles and echo chambers, limiting content diversity (Pariser, 2011). To counteract this, many systems incorporate novelty and diversity metrics (Castells et al., 2015). In summary, PRS optimize content delivery through accuracy, trustworthiness, acceptance, and personalization. Future developments will emphasize transparency, user control, mitigating filter bubbles, and leveraging context-aware computing for better recommendations (Zhang et al., 2020).

2.3. E-commerce shopping & returns

When customers experience dissatisfaction with a product they have bought or discover that it falls short of their expectations, they frequently form an intention to return it and make appropriate choices. Chen et al. (2020) described return intention as a psychological state following dissatisfaction with a specific product, representing a post-purchase reaction. The rise of e-commerce has made online shopping mainstream, yet high return rates pose a significant challenge for businesses (Ramanathan, 2011). Studies indicate that return policies, logistics efficiency, and product information transparency influence consumer purchase decisions and loyalty (Petersen & Kumar, 2015). Key factors include purchase intention-the likelihood of making a purchase (Davis, 1989); return behavior-the frequency and reasons for product returns (Wood, 2001); return policy influence-the influence of return policies on consumer purchasing behaviors (Janakiraman et al., 2016); and customer satisfaction-the influence of return procedures and customer support on consumer experience (Hjort et al., 2019).

In online shopping, consumers rely solely on website-provided information since they cannot physically inspect products, which may lead to misperceptions if the product does not match its description, ultimately resulting in dissatisfaction (Rahman et al., 2020). The prominence of returns in e-commerce is driven by factors such as impulsive purchases, unmet expectations, and lenient return policies designed to reduce perceived shopping risks and encourage sales. While these policies enhance consumer trust, they also contribute to higher return rates, making return management a critical aspect of e-commerce operations. In order to tackle these obstacles, individualized recommendation systems serve a pivotal function in enhancing the consumer shopping experience and augmenting organizational efficacy. Through the utilization of user data, these systems offer accurate product recommendations, thereby enhancing engagement, conversion rates, and customer loyalty (Stalidis et al., 2023; Zhang et al., 2024; Kanth et al., 2024). Additionally, they integrate with digital marketing strategies to promote alternative and sustainable products, contributing to both sales growth and brand development. While high return rates stem from consumer behavior and shopping patterns, optimizing recommendation algorithms and return policies allows e-commerce platforms to enhance competitiveness and foster long-term, sustainable growth.

2.4. Immersion, perceived value & purchase behavior

The connection among immersion, perceived value, and purchasing behavior represents a multifaceted dynamic explored in numerous contexts, such as mobile commerce, social commerce, and luxury brand marketing. Immersion refers to a state of deep engagement in a digital environment (Jennett et al., 2008) and can be enhanced through virtual fitting rooms, 3D product displays, and AR technologies, boosting consumers' purchase intentions (Flavián et al., 2019). In mobile short-video applications, immersive experiences increase perceived value, which in turn enhances purchase intentions (Hewei and Benetreau, 2022). Perceived value, encompassing utilitarian, hedonic, and social dimensions, is a key predictor of purchasing behavior. In social commerce, utilitarian value drives purchase intentions, while hedonic value enhances satisfaction, indirectly boosting purchase behavior (Gan and Wang, 2017). In luxury brands, functional and symbolic value strengthen brand attachment, increasing purchase intentions (Petravičiūtė et al., 2021). The perceived value serves as a mediator in the interaction between immersion and consumer purchasing behavior, given that immersive experiences augment perceived value, which subsequently results in heightened purchase intentions (Hewei and Benetreau, 2022). In summary, immersion enhances perceived value, which in turn drives purchasing behavior, highlighting its key mediating role in consumer decision-making. Understanding this relationship can help marketers design more effective strategies.

2.5. Hypotheses development

This section proposes hypotheses based on the DeLone and McLean Information Systems Success Model and prior empirical findings. To enhance clarity and avoid redundancy, we consolidate related constructs under unified conceptual rationales.

2.5.1. Quality of personalized recommendation systems and consumer responses

Personalized recommendation systems, fueled by AI and big data, are crucial for improving consumer choices and shopping experiences. These systems tailor product or service suggestions based on user preferences, past behavior, and real-time data, thereby influencing perceived value-defined as the balance between benefits received and costs incurred (Zeithaml, 1988; Tam and Ho, 2006). The efficacy of personalized recommendation systems is categorized into three primary dimensions: information quality, system quality, and service quality. Information quality refers to the accuracy, relevance, completeness, and timeliness of recommendations (Xu et al., 2020), which can reduce decision-making effort and build consumer trust (Xiao and Benbasat, 2007). System quality includes usability, responsiveness, and reliability, enhancing user engagement and perceived utility (DeLone and McLean, 2003; Kim et al., 2021; Sundar et al., 2024). Service quality includes personalization, responsiveness, and customer support-factors that enhance the overall shopping experience (Parasuraman et al., 1988; Wu et al., 2022; Zhou et al., 2020). Quality dimensions affect perceived value and purchase intention. Therefore, we propose.

H1. The quality of personalized recommendation systems positively influences perceived value.

H1a. Information quality positively influences perceived value.

H1b. System quality positively influences perceived value.

H1c. Service quality positively influences perceived value.

H2. The quality of personalized recommendation systems positively influences purchase intention.

H2a. Information quality positively influences purchase intention.

H2b. System quality positively influences purchase intention.

H2c. Service quality positively influences purchase intention.

2.5.2. *Immersion as a driver of perceived value and intention*

Immersion refers to a deep psychological and emotional involvement in the online shopping process. Drawing on Flow Theory and the Experience Economy framework, immersive experiences-such as virtual try-ons, interactive product demos, or visually engaging interfaces-can heighten engagement and perceived value (Csikszentmihalyi, 1990; Pine II and Gilmore, 1999; Flavián et al., 2019; Hewei and Benetreau, 2022). However, in categories like fashion, purchase decisions may also depend on tangible qualities such as fit, texture, or price sensitivity, which may dilute the effect of immersion on actual buying behavior (Liu and Shrum, 2009). Thus, we hypothesize.

H3. Immersion positively influences perceived value.

H4. Immersion positively influences purchase intention.

2.5.3. *Value, satisfaction, and intention linkage*

Perceived value-consumers' cognitive evaluation of the benefits received relative to what is given up-has been shown to influence both pre- and post-purchase stages. It is a key predictor of purchase intention (Gan and Wang, 2017; Tang and Wu, 2024), yet its effect on post-purchase satisfaction may weaken in high-risk categories like fashion, where perceived value formed online might not align with the received product (Rahman et al., 2020). Purchase intention itself has been positively linked to satisfaction when expectations are met during product use (Suastiari and Mahyuni, 2022). Accordingly, we propose.

H5. Perceived value positively influences purchase intention.

H6. Purchase intention positively influences post-purchase satisfaction.

H7. Perceived value positively influences post-purchase satisfaction.

2.5.4. *Satisfaction and return intention*

Post-purchase satisfaction, defined as the degree to which the actual product experience meets prior expectations, has a direct bearing on consumer loyalty and return behaviors (Oliver, 1980; Anderson and Sullivan, 1993). In online apparel shopping, mismatches in size, color, or material often lead to dissatisfaction, which increases return intention (Le et al., 2019; Park, 2022). High satisfaction reduces the cognitive dissonance that motivates returns, positioning satisfaction as a key determinant of retention behavior. Thus, we propose.

H8. Post-purchase satisfaction negatively influences return intention.

2.6. *III methodology*

This research utilizes a quantitative methodology based on the revised DeLone and McLean (2003) Information Systems Success Model to explore the impact of the quality of personalized recommendation systems on consumer decision-making processes within the realm of e-commerce. By integrating constructs such as perceived value, purchase intention, and post-purchase satisfaction-alongside newer dimensions like immersion and return intention-the model captures both cognitive evaluations and behavioral responses. The methodology includes a two-stage data collection process and uses validated measurement scales adapted for the context of online fashion retail.

2.7. *Research framework*

The theoretical framework is meticulously designed to analyze the impact of three components of system quality-namely, information quality, system quality, and service quality-on consumer responses. It leverages prior implementations of the IS Success Model within the domain of e-commerce research while augmenting it by integrating immersion as a fundamental experiential variable. Immersion is expected to affect both perceived value and purchase intention. The framework also includes post-purchase satisfaction and return intention to reflect the full consumer journey from recommendation to consumption outcome. Although the model presents a sequential path from system quality to perceived value and then to purchase intention, this study does not aim to formally test perceived value as a mediating variable. The primary analytical focus remains on examining the direct effects among the key constructs. The proposed research framework is illustrated in Fig. 1.

3.2 Operational definition and measurement.

This study employed a purposive sampling strategy to target online fashion consumers who had prior experience with personalized recommendation systems. The sample is not intended to be nationally representative. Notably, over two-thirds of participants were female, and the majority were users of Shopee or Momo-two of Taiwan's leading e-commerce platforms. These demographic and platform-specific characteristics reflect real-world usage patterns but may limit the generalizability of findings to other populations or regions.

> All constructs in this study were measured using established scales from prior literature, with minor contextual adaptations to reflect the online fashion retail environment. All measurement items were translated from English to Chinese using the back-translation procedure recommended by Brislin (1970), to ensure cross-linguistic validity. This process involved an initial forward translation by a bilingual expert, followed by a blind back-translation by another independent bilingual translator. Discrepancies between the original and back-translated versions were then reconciled through discussion to ensure semantic equivalence.

The concept of the PRS encompasses three principal dimensions: information quality, which pertains to the precision, comprehensiveness, and pertinence of the suggested content; system quality, indicating the usability, responsiveness, and technical performance of the recommendation interface; and service quality, which reflects the level of customization, interactivity, and support provided throughout the recommendation process. Perceived value captures consumers' evaluations of the trade-off between what they gain and what they give up during the shopping experience. Immersion denotes the cognitive and emotional engagement experienced by users while interacting with personalized recommendations. The behavioral outcome variables-purchase intention, post-purchase satisfaction, and return intention-reflect distinct phases of the consumer journey and were assessed utilizing a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

The proposed model includes seven latent constructs and twelve structural paths, indicating a moderate level of complexity. To ensure the adequacy of the sample size for PLS-SEM analysis, we applied multiple evaluation criteria.

First, based on general SEM guidelines, models of this complexity typically require a sample size between 200 and 300 to ensure reliable

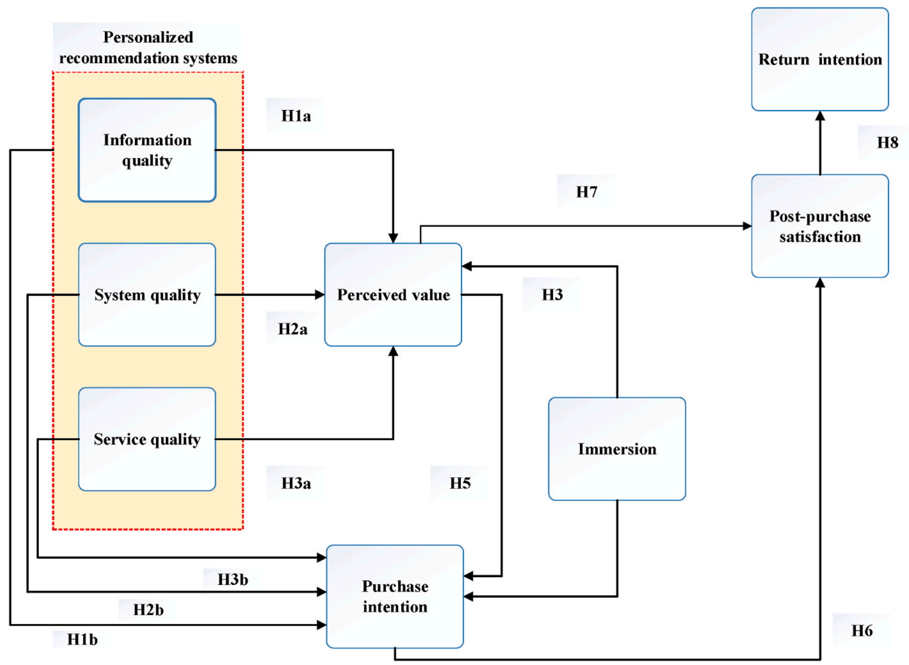

Fig. 1. Research framework.

parameter estimation and sufficient statistical power (Kline, 2016). Our final matched sample of 299 respondents therefore falls within this acceptable range.

Second, a G*Power 3.1 analysis for linear multiple regression (effect size $f^2 = 0.15$, $\alpha = 0.05$, power $= 0.95$, and four predictors) yielded a minimum recommended sample size of 129, again well below our actual sample size.

Based on above statements, these assessments collectively confirm that our sample is sufficient and appropriate for robust and valid modeling using SmartPLS 4.0.

Additionally, a full list of the measurement items, including item wordings and original sources, is provided in Appendix A. For each construct, we specified whether the items were directly adopted or contextually adapted from prior validated instruments. The adaptation process involved tailoring the language and content to fit the online fashion e-commerce context. All scales were originally developed in English and were translated into Chinese using Brislin's (1970) back-translation procedure to ensure semantic equivalence and cross-cultural validity. Discrepancies between original and back-translated versions were reviewed and resolved by the research team.

The analysis proceeded in the following steps: (1) Data screening and cleaning, including attention-check filters and removal of inconsistent cases; (2) Confirmatory factor analysis (CFA) to assess internal consistency, convergent validity, and discriminant validity using composite reliability (CR), AVE, and Fornell–Larcker criterion; (3) Structural equation modeling (SEM) to test the hypothesized relationships among constructs. Statistical procedures included data preprocessing and reliability checks in SPSS, followed by model estimation and hypothesis testing in SmartPLS 4.0. Mediation effects were evaluated using the default bootstrapping procedure with 5000 resamples, which provides bias-corrected confidence intervals for indirect effects and ensures robust significance testing (Preacher and Hayes, 2008).

3. IV results and analyses

This study implemented a two-phase survey methodology to examine how personalized recommendation systems influence consumer behavior in online fashion retail. In Phase 1, conducted between November 20 and December 11, 2024, a total of 609 responses were collected through both online and printed questionnaires. After applying a validity check using an attention-screening item from the immersion scale (e.g., "I don't need to wear a mask in a bank"), 589 responses were retained for further analysis. Phase 2 was conducted between February 17 and March 3, 2025, during which follow-up questionnaires were distributed to the same group of 589 participants to track actual purchase behavior and post-purchase perceptions. A total of 385 responses were received in this phase. Among them, 86 participants were excluded based on a filtering question assessing actual purchase behavior: "Did you actually make a purchase within the past three months due to the personalized recommendation services provided by the website?" An additional 15 responses were removed due to unmatched identifiers or inconsistencies between the two datasets. This process yielded a final matched sample of 299 valid responses, serving as the analytical foundation for subsequent model testing and validation.

3.1. *Sample characteristics*

Among the valid respondents, 65 % were female, with most aged 21–35. The majority held a university or junior college degree (67 %), and 36 % had a monthly disposable income above NT$15,001. Table 1, Over half (53 %) lived in the Taipei metropolitan area and browsed e-commerce platforms for 1–2 h daily. 66 % of consumers purchased fashion items within 1–3 months, indicating short decision cycles. Shopee was the preferred platform (73 %), showing stronger engagement than Momo (27 %). Under personalized recommendations, 78 % made actual purchases, mainly clothing and accessories. Non-purchasers cited low interest (17 %) and budget limits (11 %). While most preferred products priced between NT$300–700, 61 % reported post-purchase dissatisfaction due to appearance mismatch (30 %) or quality issues (18 %). 25 % considered returns despite satisfaction, suggesting possible overuse of lenient return policies. Of those who didn't return, 34 % found the process complicated, Tables 1a and 19 % accepted dissatisfaction. In the follow-up, 56 % of dissatisfied users initiated returns, highlighting the need for better return procedures and customer support.

Table 1
Confirmatory factor analysis.

Construct/Dimension	Items	Mean	Std. deviation	Factor loading	CR	AVE	Cronbach's α
Information Quality		2.129	0.723		0.914	0.541	0.893
Content	I1	2.033	0.704	0.867	0.882	0.714	0.799
	I2	2.050	0.686	0.882			
	I3	1.977	0.683	0.784			
Format	I4	2.241	0.766	0.777	0.854	0.661	0.744
	I5	2.064	0.690	0.816			
	I6	2.211	0.732	0.846			
Accuracy	I7	2.211	0.732	0.798	0.852	0.657	0.738
	I8	2.224	0.695	0.854			
	I9	2.251	0.782	0.778			
System Quality	S1	2.171	0.752	0.791	0.879	0.646	0.817
	S2	2.114	0.691	0.834			
	S3	2.033	0.709	0.832			
	S4	2.003	0.658	0.756			
Service Quality		2.297	0.776		0.901	0.566	0.872
Customer service	SQ1	2.304	0.793	0.756	0.792	0.864	0.615
	SQ2	2.194	0.725	0.805			
	SQ3	2.435	0.806	0.765			
	SQ4	2.274	0.736	0.801			
Privacy	SQ5	2.348	0.802	0.798	0.802	0.881	0.713
	SQ6	2.388	0.801	0.882			
	SQ7	2.308	0.750	0.851			
Immersion	IM1	2.348	2.348	0.815	0.876	0.908	0.663
	IM2	2.214	2.214	0.79			
	IM3	2.314	2.314	0.829			
	IM4	2.314	2.314	0.843			
	IM5	2.181	2.181	0.794			
Perceived Value					0.924	0.55	0.909
Emotional value	PV1	2.385	0.735	0.836	0.867	0.684	0.769
	PV2	2.411	0.791	0.846			
	PV3	2.167	0.704	0.799			
Social value	PV4	2.264	0.769	0.855	0.896	0.742	0.826
	PV5	2.358	0.808	0.855			
	PV6	2.428	0.809	0.874			
Economic value	PV7	2.201	0.685	0.815	0.884	0.657	0.826
	PV8	2.227	0.667	0.825			
	PV9	2.194	0.662	0.821			
	PV10	2.281	0.701	0.780			
	B6	2.161	0.705	0.772			
Purchase Intention	B2	2.154	0.712	0.831	0.868	0.622	0.797
	B3	2.221	0.731	0.782			
	B4	2.154	0.663	0.770			
	B6	2.161	0.705	0.772			
Post-purchase satisfaction		2.393	0.776		0.903	0.608	0.871
Consistency	PS1	2.161	0.705	0.828	0.865	0.682	0.766
	PS2	2.371	0.690	0.868			
	PS3	2.431	0.727	0.779			
Overall evaluation	PS4	2.538	0.816	0.816	0.884	0.718	0.803
	PS5	2.408	0.791	0.869			
	PS6	2.304	0.797	0.856			
Return intention	R1	2.291	0.847	0.771	0.872	0.631	
	R2	1.977	0.813	0.876			0.805
	R3	2.194	0.817	0.749			

3.2. Reliability and validity

CFA was performed to evaluate the reliability and validity of the measurement model. As shown in Table 2, discriminant validity was assessed using the Fornell–Larcker criterion. The square roots of the Average Variance Extracted (AVE) values are presented on the diagonal, while the off-diagonal elements represent inter-construct correlations. For all constructs, the square root of the AVE exceeds the corresponding correlations with other constructs, indicating that discriminant validity is established (Fornell and Larcker, 1981).

To further assess discriminant validity, this study employed the Heterotrait–Monotrait Ratio (HTMT) criterion. The results show that most HTMT values fall below the recommended threshold of 0.85, indicating acceptable discriminant validity overall. Although the HTMT value between perceived value and purchase intention reached 0.914-slightly exceeding the conventional cutoff-some scholars (e.g., Henseler et al., 2015) suggest that a more lenient threshold of 0.90 may be acceptable (See Table 3). Based on this standard, all constructs in this study can be considered to have passed the HTMT test, and the overall measurement model can thus be regarded as satisfying the requirements for discriminant validity.

The slightly elevated HTMT value may reflect a close psychological linkage between perceived value and purchase intention in practical contexts. For instance, participants who perceive recommended

Table 2
Discriminant validity matrix[c] (Fornell–Larcker Criterion).

Construct	(1)	(2)	(3)	(4)	(5)	(6)
Immersion (1)	**0.81**[a]					
Perceived value (2)	0.77[b]	**0.89**[a]				
System quality (3)	0.60[b]	0.66[b]	**0.80**[a]			
Post-purchase satisfaction (4)	0.02[b]	−0.06[b]	0.02[b]	**0.93**[a]		
Purchase intention (5)	0.68[b]	0.79[b]	0.66[b]	−0.11[b]	**0.76**[a]	
Return intention (6)	−0.06[b]	−0.07[b]	−0.07[b]	0.14[b]	−0.06[b]	**0.79**[a]

[a] At a significance level of 0.01 (two-tailed), the values on the diagonal represent the square root of the AVE (Average Variance Extracted) for each variable.
[b] Off-diagonal values represent Pearson correlation coefficients between constructs.
[c] In the PRS construct, system quality is reflective, while information quality and service quality are formative.

Table 3
Heterotrait–Monotrait (HTMT) ratios for discriminant validity assessment.

Construct	(1)[a]	(2)	(3)	(4)	(5)	(6)
Immersion (1)						
Perceived value (2)	0.887					
System quality[a] (3)	0.704	0.773				
Post-purchase satisfaction (4)	0.059	0.071	0.076			
Purchase intention (5)	0.782	0.914	0.784	0.118		
Return intention (6)	0.092	0.092	0.092	0.154	0.074	

[a] In the PRS construct, system quality is reflective, while information quality and service quality are formative. Therefore, only system quality is reported in the HTMT results, since information quality and service quality are formative and excluded from discriminant validity testing using HTMT.

information as valuable may be more likely to express immediate purchase intentions. Future research could further clarify the theoretical distinctiveness between these two constructs or refine item wording to reduce conceptual overlap, thereby enhancing the precision and theoretical contribution of the measurement.

3.3. *Structural model analysis*

The structural model was rigorously assessed utilizing standardized path coefficients (β), t-values, and significance levels to empirically evaluate the proposed relationships. Among the twelve hypothesized paths, eight were statistically supported.

- The quality of information significantly influenced both perceived value ($\beta = 0.139$, $p < 0.05$) and purchase intention ($\beta = 0.063$, $p < 0.05$), thereby confirming H1a and H2a.
- The quality of the system had a notable impact on perceived value ($\beta = 0.118$, $p < 0.05$) and intention to purchase ($\beta = 0.179$, $p < 0.05$), thereby validating H1b and H2b.
- The quality of service exhibited marked positive influences on both perceived value ($\beta = 0.288$, $p < 0.05$) and purchase intention ($\beta = 0.154$, $p < 0.05$), thereby corroborating hypotheses H1c and H2c.
- The concept of immersion has been shown to have a substantial impact on perceived value ($\beta = 0.417$, $p < 0.05$), thereby providing support for hypothesis H3.
- The perceived value exerted a notable positive influence on the intention to purchase ($\beta = 0.386$, $p < 0.05$), thus confirming H5.
- Post-purchase satisfaction negatively influenced return intention ($\beta = -0.13$, $p < 0.05$), supporting H8.

However, four hypotheses were not supported.

- Immersion had no notable impact on purchase intention ($\beta = 0.009$, $p > 0.05$), therefore H4 was not validated.
- Neither the perceived value ($\beta = 0.02$, $p > 0.05$) nor the intention to purchase ($\beta = -0.01$, $p > 0.05$) had a significant impact on post-purchase satisfaction, thus not providing support for H6 and H7.

These findings (see Table 4) indicate that the quality of the personalized recommendation system (information, system, and service quality) and immersion primarily drive perceived value and purchase intention. However, their influence does not extend to post-purchase satisfaction, suggesting other factors may mediate or moderate satisfaction and return behaviors. Notably, only post-purchase satisfaction demonstrated a significant negative association with return intention, highlighting its critical role in reducing returns (see Fig. 2).

3.4. *Mediation analysis*

According to Fig. 2, this study reveals two significant mediation effects. All indirect effects were tested using bootstrapping with 5000 resamples to obtain bias-corrected confidence intervals, ensuring robust estimation within the structural model. The results show that PRS quality-including information, system, and service quality-indirectly influences purchase intention through perceived value. Additionally, immersion affects purchase intention solely through perceived value, as its direct effect is non-significant while the indirect path via perceived value is statistically supported. These results underscore perceived value as a central cognitive mechanism that translates both technical quality and experiential engagement into behavioral intention in the context of fashion e-commerce.

To further unpack these mediation dynamics, the following sections examine the two indirect pathways in detail: (1) how PRS quality influences purchase intention through perceived value, and (2) how immersion impacts purchase intention via the same mediating route.

1. PRS Quality → Perceived Value → Purchase Intention

According to the mediation analysis results in Table 5, all three PRS quality components—information quality, system quality, and service quality—exert significant indirect effects on purchase intention through perceived value, with 95 % confidence intervals that do not include zero. Specifically, service quality shows the strongest indirect effect ($\beta = 0.133$, $p < 0.001$, 95 % CI [0.070, 0.197]), followed by information quality ($\beta = 0.069$, $p = 0.017$, 95 % CI [0.020, 0.134]) and system quality ($\beta = 0.056$, $p = 0.046$, 95 % CI [0.003, 0.115]). At the same time, Table 4 confirms that all three components also have significant direct effects on purchase intention: information quality ($\beta = 0.063$, $t = 2.053$, $p < 0.01$), system quality ($\beta = 0.179$, $t = 2.053$, $p < 0.01$), and service quality ($\beta = 0.154$, $t = 2.273$, $p < 0.01$). The coexistence of significant direct and indirect effects indicates that perceived value functions as a partial mediator. Among the three components, service quality exerts the most balanced and substantial influence across both pathways, while system quality has the strongest direct impact despite a weaker indirect effect. These results underscore the cognitive role of perceived value in linking quality perceptions to consumer behavioral intentions in personalized recommendation contexts (Choi et al., 2017; Wang et al., 2024).

2. Immersion → Perceived value →Purchase intention

As shown in Tables 4 and 5, immersion significantly influences perceived value ($\beta = 0.417$, $t = 8.584$), and perceived value significantly predicts purchase intention ($\beta = 0.386$, $t = 4.570$). However, the direct path from immersion to purchase intention is not significant ($\beta = 0.090$, $t = 1.054$). In contrast, Table 5 reveals a significant indirect effect of immersion on purchase intention via perceived value ($\beta = 0.196$, $p < 0.001$, 95 % CI [0.128, 0.288]). These results clearly indicate that perceived value fully mediates the relationship between immersion and

Table 4
Summary of path analysis.

Hypothesis	Path	Standardized estimate	S.D	t-value	Result
H1a	Information quality→Perceived value	0.139***	0.064	2.158	Supported
H1b	System quality→Perceived value	0.118***	0.06	1.972	Supported
H1c	Service quality→Perceived value	0.288***	0.055	5.217	Supported
H2a	Information quality→Purchase intention	0.063***	0.074	2.053	Supported
H2b	System quality→ Purchase intention	0.179***	0.087	2.053	Supported
H2c	Service quality→ Purchase intention	0.154***	0.068	2.273	Supported
H3	Immersion- > Perceived value	0.417***	0.049	8.584	Supported
H4	Immersion- > Purchase intention	0.090	0.086	1.054	Not supported
H5	Perceived value- > Purchase intention	0.386***	0.084	4.57	Supported
H6	Purchase intention- > Post-purchase satisfaction	−0.01	0.097	1.042	Not supported
H7	Perceived value- > Post-purchase satisfaction	0.02	0.102	0.193	Not supported
H8	Post-purchase satisfaction- > Return intention	−0.13***	0.062	2.15	Supported

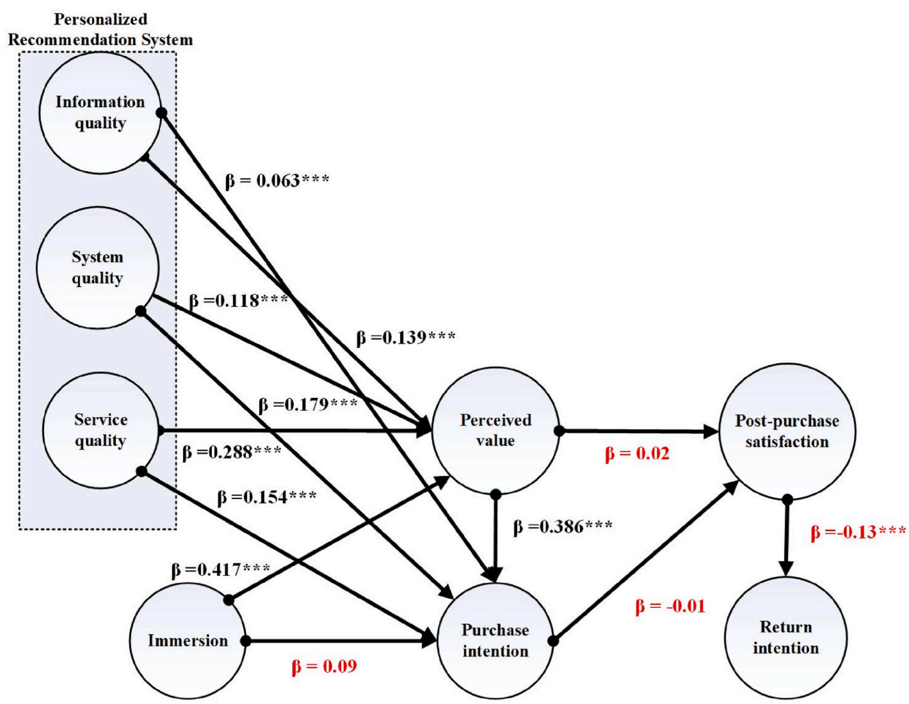

Fig. 2. Path analysis (PLS-SEM using SmartPLS 4.0).

Table 5
Indirect effects and significance testing via bootstrapping.

Path	Indirect effect	P-value	2.5 %	97.5 %
Information quality→ Perceived value → Purchase intention	0.069	0.017	0.02	0.134
System quality→ Perceived value → Purchase intention	0.056	0.046	0.003	0.115
Service quality→ Perceived value→ Purchase intention	0.133	0	0.07	0.197
Immersion→Perceive value→Purchase intention	0.196	0	0.128	0.288

purchase intention. This finding aligns with previous research (Ltifi, 2018; Hewei and Youngsook, 2021; Hewei and Benetreau, 2022), which suggests that in fashion e-commerce, immersive tools such as AR try-ons and 3D fitting rooms enhance emotional engagement but rarely lead directly to purchases. Instead, consumers tend to evaluate whether a product is “worth it” by assessing expected quality, personal style alignment, and price fairness. Since apparel purchases involve high tactile and fit uncertainty, purchase intentions are shaped more by perceived value than by emotional experience alone. Immersion enhances engagement, but it only effectively drives purchase intention when it translates into cognitive value-through realistic visuals, detailed sizing information, and transparent return policies.

V Discussion.

Building on the DeLone and McLean (2003) Information Systems Success Model, this study examined how the quality of personalized recommendation systems-captured by information, system, and service quality-affects consumers’ perceived value, purchase intention, post-purchase satisfaction, and return intention. Immersion was included as a psychological engagement variable to capture richer user experience during the online shopping process. The findings offer a more nuanced understanding of consumer behavior across multiple stages of the fashion e-commerce decision journey.

1. Recommendation-system quality shapes pre-purchase cognitions and intentions

Echoing classic IS-success work (DeLone and McLean, 2003) and recent e-commerce evidence (Kim et al., 2021; Wu et al., 2022), all three quality dimensions-information, system, and service-significantly enhance perceived value, while system and service quality additionally stimulate purchase intention (Noronha and Rao, 2017; Yu et al., 2024). These findings confirm that usability, reliability, and responsive support are as critical as algorithmic accuracy in early decision making (Davis, 1989; Xiao and Benbasat, 2007; Gill et al., 2024). For platform managers, investments in interface speed, intuitive design, and service responsiveness can therefore translate directly into higher conversion rates. This suggests that multi-dimensional quality-not just technical precision-is essential to influencing purchase-related behavior.

4. Immersion enhances perceived value but stalls before the “buy” button

Anchored in Flow Theory (Csikszentmihalyi, 1990) and the Experience Economy paradigm (Pine II and Gilmore, 1999), immersion demonstrated a strong positive influence on perceived value, consistent with prior research on experiential and affective engagement (Schmitt, 1999; Holbrook, 2006; Flavián et al., 2019; Hewei and Benetreau, 2022). Shoppers may delight in vivid imagery and AI-driven try-ons (Hoffman and Novak, 2009; Song et al., 2019), but still refrain from purchase because of price sensitivity, perceived risk, or choice overload (Liu and Shrum, 2009). This explains why immersion did not significantly influence purchase intention-especially in product categories like fashion where concerns over fit, material, and accuracy remain critical. We propose that immersion functions as a state-bounded affective experience: enjoyable but not always action-inducing. Future studies should explore mediators such as trust and decision confidence, and moderators like product involvement, regulatory focus, or decision fatigue, to clarify when and how immersive engagement translates into purchase behavior.

3. A cognitive-emotional disconnect: Perceived value ≠ Post-purchase satisfaction

Contrary to the dominant value-satisfaction narrative (Sweeney and Soutar, 2001; Eggert and Ulaga, 2002), the link between perceived value and post-purchase satisfaction was non-significant. In sensory-rich categories like fashion, value judgments are often formed online, while satisfaction is only assessed after tactile and visual verification (Rahman et al., 2020). Discrepancies in fabric feel, color accuracy, or fit can override earlier perceptions of value, revealing a theoretical blind spot in Expectation-Disconfirmation Theory (Oliver, 1980). This is further supported by our finding that although perceived value positively influenced purchase intention (Gan and Wang, 2017; Tang and Wu, 2024), it did not significantly affect post-purchase satisfaction. Thus, even when consumers respond favorably to recommendation systems, actual satisfaction is not guaranteed. Perceived value may act primarily as a pre-purchase motivator, while satisfaction hinges on post-purchase sensory congruence. We suggest future research refine value–satisfaction frameworks by integrating sensory realism and expectation precision. This non-significance is evident in the low path coefficients for H6 ($\beta = -0.01$, n.s.) and H7 ($\beta = 0.02$, n.s.), indicating that neither purchase intention nor perceived value significantly influenced post-purchase satisfaction. These results underscore a clear disconnect between pre-purchase evaluations and actual satisfaction, especially in sensory-driven categories like fashion. Even when consumers perceive value or intend to buy, their satisfaction depends more on the physical product experience. This highlights the need to refine value–satisfaction models to account for post-purchase disconfirmation effects.

4. Post-purchase satisfaction: The decisive brake on return intention

Our results show that post-purchase satisfaction is the sole significant predictor of return intention, supporting the Expectation-Disconfirmation Theory (Oliver, 1980), which suggests that unmet expectations lead to dissatisfaction and increased returns (Anderson and Sullivan, 1993; Le et al., 2019; Park, 2022; Janakiraman et al., 2016). This finding also aligns with research on post-decision dissonance and consumer regret (Martins et al., 2019), highlighting the need to manage post-purchase emotions through accurate product representation, virtual try-ons, and responsive after-sales support. Taken together, we offer a holistic yet cautionary insight: while pre-purchase immersion and perceived value are enhanced by system quality, they do not automatically ensure satisfaction. The psychological distance between digital persuasion and the physical reality of product experience remains a critical challenge in online retail. Thus, future e-commerce success will require more than just algorithmic refinement-it demands efforts to close the value-satisfaction gap through realistic expectation-setting, enhanced sensory simulation (e.g., virtual try-ons), and transparent product representation. By aligning pre-purchase perceptions with post-purchase realities, platforms can better reduce return intentions and improve long-term customer trust.

4.1. *Theoretical contributions*

In the realm of digital commerce, this study contributes to the intersecting domains of information systems and consumer decision-making by addressing both pre- and post-purchase stages of the consumer journey.

First, it extends the by incorporating post-purchase constructs-specifically satisfaction and return intention-thereby bridging the gap between system quality evaluation and full-cycle consumer behavior. While prior IS research has largely focused on system use and intention (Al-Fraihat et al., 2020), this study shifts the lens toward long-term outcomes, highlighting how consumers respond after the transaction is complete. Second, the study incorporates immersion as a psychological engagement variable grounded in Flow Theory (Csikszentmihalyi, 1990) and the Experience Economy framework (Pine II and Gilmore, 1999), thus enriching the IS Success Model with an experiential dimension. Results indicate that immersion significantly enhances perceived value, underscoring its role in shaping consumers’ cognitive evaluations. However, it does not directly influence purchase intention, suggesting that emotionally rich experiences, while impactful, may not always lead to transactional behaviors. This finding adds nuance to our understanding of how immersive experiences function in digital shopping environments. Third, and most critically, the study reveals an unexpected non-significant relationship between perceived value and post-purchase satisfaction. This challenges the widely held assumption that higher perceived value leads to greater satisfaction (e.g., Sweeney and Soutar, 2001; Eggert and Ulaga, 2002). Instead, our findings suggest that perceived value operates primarily as a pre-purchase cognitive assessment, influencing intention but not necessarily guaranteeing satisfaction. Particularly in fashion e-commerce, issues such as material mismatch, color deviation, and fit problems may override initial perceptions of value and lead to dissatisfaction. This cognitive–emotional disconnect highlights a theoretical blind spot in current applications of Expectation-Disconfirmation Theory (Oliver, 1980), calling for further research into contextual moderators-such as product category, expectation realism, or individual sensitivity to product attributes-to more fully explain how satisfaction is formed.

4.2. *Managerial implications*

Integrating insights from existing research and current findings, the following practices are advised for e-commerce operators seeking to reinforce customer loyalty and reduce the incidence of returns.

1. *Enhance recommendation system design and immersive browsing experience.* The analysis confirms that information, system, and service quality, alongside immersion, significantly enhance perceived value. Moreover, system and service quality are key drivers of purchase intention (Pu et al., 2011; Kim et al., 2021; Zhong and Hamouda, 2024). By offering accurate, timely, and personalized

recommendations alongside immersive experiences-such as virtual try-ons or AR/VR features-platforms can effectively increase consumer engagement and intention to purchase (Liu et al., 2020; Singh et al., 2023). Given that quality factors significantly affect perceived value, and perceived value in turn influences purchase intention, enhancing usability and user experience remains crucial for platform effectiveness.

2. *Improve product consistency and strengthen quality control.* As purchase intention does not significantly influence post-purchase satisfaction, this suggests a potential disconnect between online persuasion and actual experience. To avoid returns and dissatisfaction, platforms must ensure product descriptions are accurate and consistent, and that delivered products align with what is presented online (Tu and Dong, 2010).
3. *Address key demographic and geographic factors affecting return intention.* Female consumers typically exhibit higher return tendencies, especially in the apparel sector. Additionally, customers in remote regions (e.g., eastern Taiwan and offshore islands) show higher return rates, likely due to gaps between product expectations and logistical constraints. Platforms need to offer local support, customized logistics, and better product details to lower returns and shipping costs. Additionally, targeted strategies according to platform traits could enhance results. For instance, Shopee users, who tend to be more price-sensitive and promotion-driven, may benefit from clearer product visuals, concise discount displays, and simplified return interfaces. In contrast, Momo users, who are often more brand- and quality-conscious, may respond better to in-depth product information, verified user reviews, and premium service assurances. Recognizing these usage patterns can help platforms optimize consumer touchpoints and reduce mismatches between expectations and actual experience.
4. *Streamline return procedures and strengthen after-sales services.* Transparent return policies and responsive customer service can significantly boost consumer trust and satisfaction (Javed et al., 2020; Parasuraman et al., 1988), while also reducing return intentions.
5. *Leverage customer data to optimize recommendation algorithms.* Ongoing optimization of algorithms using user behavior and feedback improves recommendation accuracy and personalization, minimizing mismatches between consumer needs and suggestions (Adomavicius and Tuzhilin, 2005; Kanth et al., 2024).

4.3. Limitations and future works

While this study offers both practical and theoretical contributions, several limitations must be acknowledged:

1. This study primarily recruited Taiwanese consumers, most of whom were female and regular users of Shopee and Momo-two leading fashion e-commerce platforms in Taiwan. While this reflects local consumption patterns (Zeithaml, 1988; Kotler and Keller, 2015), it may limit the generalizability of the findings to other populations, platforms, and regions. The gender imbalance may introduce bias, as female consumers tend to show stronger emotional involvement, higher aesthetic sensitivity, and more frequent return behavior in fashion purchases (Belleau et al., 2008; Herter et al., 2014). Prior studies also highlight the role of women in driving online purchases through relational and emotional value (Fang et al., 2016; Belleau et al., 2008). Additionally, the follow-up response rate was modest, and users of smaller or international platforms were underrepresented. Future studies are encouraged to expand sample size and increase diversity across gender, platform, and geography to enhance statistical power and external validity (Wilfling et al., 2022).

2. The second-phase questionnaire was distributed just two weeks after the first phase, which may have introduced bias in responses to questions such as “Have you purchased fashion items within the last three months?” As shown in a majority of consumers had made purchases within one month, potentially affecting the objectivity and precision of responses. Future research should refine timing control and survey design accordingly.

3. The sample had a high proportion of female respondents, which may reflect a greater tendency among women to purchase fashion products online. However, this gender imbalance may limit the representativeness of the findings for the broader Taiwanese population. It is advisable that subsequent investigations strive for a more equitable gender representation in order to augment the diversity of the sample.
4. This research employed a cross-sectional methodology, which limits the ability to observe behavioral changes over time. Future research could consider longitudinal or experimental methods to better assess causality (Jennett et al., 2008).
5. The current model did not include other potentially important mediating or moderating variables, such as trust, perceived risk, or product involvement. Future research could integrate these psychological constructs to build a more comprehensive model (Tintarev and Masthoff, 2015; Liu and Shrum, 2009).
6. This study did not examine how various recommendation techniques-including those driven by user behavior (e.g., collaborative filtering), item characteristics (e.g., content-based methods), or a combination of both-affect outcomes. Future research could investigate which algorithmic approach yields superior user responses (Mohanty et al., 2022; Ricci et al., 2015).
7. The study did not address the moral hazard that may arise from lenient return policies, such as encouraging a “buy now, think later” mentality. Future research should explore how flexible return policies might reduce consumers’ sense of purchase responsibility (Janakiraman et al., 2016).
8. Although the model confirms significant direct paths from PRS quality to perceived value and from perceived value to purchase intention, this study did not formally test perceived value as a mediator. The focus of our structural model was to examine direct relationships, not mediation mechanisms. While the observed sequential effects imply a potential indirect pathway, formal mediation analysis (e.g., using bootstrapping or PROCESS macro) was beyond the scope of this study. Future research is encouraged to conduct mediation testing to rigorously assess the presence and strength of such effects.
9. Future studies may explore how localized return policies-tailored to platform-specific user expectations and regional cultural norms-could reduce unnecessary returns while maintaining customer satisfaction. Additionally, segmentation strategies based on factors such as shopping frequency, device use, or purchase motivations could help platforms personalize both recommendations and after-sales services.
10. Since consumers from different cultural backgrounds may respond differently to recommendation systems, and various types of algorithms (such as collaborative filtering or content-based approaches) might produce different outcomes, this represents a key limitation of the present study. To address this, future research is encouraged to incorporate algorithmic comparisons and consider cultural background as a moderating variable. These additions will help to deepen the applicability of the model and assess its robustness across diverse technological and cultural contexts.

While the study provides new insights into the influence of recommendation system quality on consumer decision-making, several limitations-particularly the gender bias and platform specificity-may restrict the generalizability of the results. These limitations may also affect the external validity and cross-platform applicability of the findings. Future research should address these issues by including more gender-balanced and demographically diverse samples, incorporating multiple types of e-commerce platforms (e.g., Amazon, Taobao), and conducting cross-country comparisons. Such efforts would enhance the robustness and applicability of the model in broader contexts.

5. VI conclusions

This research investigated the quality of personalized recommendation systems, encompassing the dimensions of information, system, and service-including information, system, and service dimensions-affects consumers' perceived value, purchase intention, post-purchase satisfaction, and return intention in the context of fashion e-commerce. The findings indicate that high-quality recommendation systems significantly enhance perceived value and purchase intention, while immersion notably strengthens perceived value through deeper user engagement. However, the factors that influence consumers before purchase do not necessarily guarantee satisfaction afterward, as the study found no significant effect of perceived value or purchase intention on post-purchase satisfaction. This suggests that even when consumers are motivated to buy, their satisfaction may still be influenced by the product's actual performance and alignment with expectations. Notably, post-purchase satisfaction was the only factor that significantly reduced return intention, emphasizing its critical role in shaping post-purchase behavior.

CRediT authorship contribution statement

Hui-Chiung Lo: Methodology, Data curation, Conceptualization. **Wen-Jung Chang:** Writing – review & editing, Visualization. **I-Hung Chen:** Writing – original draft, Formal analysis, Data curation.

Declaration of competing interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper. This research was conducted independently, and the authors have no financial, commercial, legal, or professional relationships with any organizations or individuals that could have influenced the content or outcomes of this work. All funding sources, if any, have been properly acknowledged in the relevant section. The views expressed in this article are solely those of the author(s) and do not necessarily reflect the views of any affiliated institutions.

Appendix. Questionnaire

Information Quality

I1. The personalized recommendation platform provides comprehensive information that enables me to find what I am looking for during the search process.

I2. The personalized recommendation platform presents clear information that helps me understand the content being displayed.

I3. The personalized recommendation platform delivers information in a way that allows me to identify which content is important to me.

I4. The personalized recommendation platform offers the latest and trendiest fashion information.

I5. The personalized recommendation platform provides rich and diverse fashion information, such as size, color, and estimated delivery time.

I6. The fashion information presented on the personalized recommendation platform is well-organized and properly formatted.

I7. The fashion information provided by the personalized recommendation platform is highly accurate.

I8. The information provided by the personalized recommendation platform is trustworthy.

I9. The personalized recommendation platform can accurately locate what I want by using relevant keywords.

System Quality.

S1. The interface of the personalized recommendation system is easy to browse and allows me to quickly scan through the content.

S2. The interface design of the personalized recommendation system is user-friendly, making the operation feel smooth and intuitive.

S3. The functions provided by the personalized recommendation system are generally acceptable and useable by most people.

S4. The interface of the personalized recommendation system is simple and easy to use.

Service Quality.

SQ1. Vendors registered on the personalized recommendation platform do not provide misleading information to the platform.

SQ2. Using the personalized recommendation platform allows access to professional services.

SQ3. The personalized recommendation platform prioritizes my needs.

SQ4. Currently, I am satisfied with the customer service provided by the staff of the personalized recommendation platform.

SQ5. I feel confident entering my personal information on the personalized recommendation platform.

SQ6. The personalized recommendation platform does not disclose or misuse personal information for private gain.

SQ7. The platform applies high standards when reviewing registered vendors to prevent customers from experiencing unfair harm.

Immersion.

IM1. Using the personalized recommendation platform makes me lose track of time and become fully absorbed in the experience.

IM2. The personalized recommendation platform creates a pleasant browsing atmosphere that I enjoy.

M3. The personalized recommendation platform captures my attention and makes me feel excited.

IM4. Using the personalized recommendation platform gives me a pleasant and enjoyable feeling.

IM5. I have a positive impression of the personalized recommendation platform after using it.

Perceived value.

PV1. Using the personalized recommendation platform feels surprising and enjoyable.

PV2. The platform enhances my overall sense of well-being.

PV3. My experience with the personalized recommendation platform is pleasant and fulfilling.

PV4. Using the platform helps me build a favorable brand image.

PV5. Using the platform allows me to gain approval or recognition from others.

PV6. The platform gives me a sense of belonging by making me feel connected with others.

PV7. The prices displayed on the personalized recommendation platform are reasonable.

PV8. The time I spend on the platform is definitely worthwhile.

PV9. The products I purchase through the platform meet my expectations.

PV10. The actual products I purchase through the platform give me a sense of great value for money.

Purchase intention.

PI1. If my budget allows, I will definitely purchase products recommended by the personalized recommendation platform.

PI2. Compared to other e-commerce platforms, this personalized recommendation platform is my first choice when shopping online.

PI3. I am interested in exploring other products recommended by the personalized recommendation platform.

PI4. I am willing to repurchase products recommended by the personalized recommendation platform.

PI5. I will continue to pay attention to the future recommendations and related information provided by the platform.

PI6. I am willing to promote the personalized recommendation platform to others.

Post-purchase satisfaction.

PS1. The products I received from the personalized recommendation platform met my expectations.

PS2. I feel very satisfied with the products I received from the personalized recommendation platform.

PS3. The entire process of receiving products from the personalized recommendation platform left a lasting impression on me.

Overall, PS4. Overall, receiving products from the personalized recommendation platform made me feel extremely pleased.

PS5. Purchasing products from the personalized recommendation platform was a good decision.

PS6. I enjoy shopping on the personalized recommendation platform.

Return intention.

RI1. If the product I receive differs in appearance or color from how it was presented on the website, I will want to return it.

RI2. If the size or fit of the product I receive is different when I try it on, I will want to return it.

RI3. If the texture of the product I receive feels different from what I expected, I will want to return it.

RI4. If the product I receive appears to be a counterfeit, I will want to return it.

RI5. If I have not received the product and the waiting time exceeds what I can tolerate, I will want to cancel or return the order.

RI6. If the return process is too complicated, I will not want to return the product.

RI7. If my family or friends disapprove of the product's value, I will consider returning it.

Data availability

The data that has been used is confidential.

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